

A Joint Game-Theoretic Interference Coordination Approach in Uplink Multi-Cell OFDMA Networks

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Abstract In this paper, we present a joint game-theoretic approach to perform inter-cell interference coordination in uplink multi-cell orthogonal frequency division multiple access networks. The coordinated user scheduling and power allocation are considered simultaneously. We prove the existence of the joint-strategy Nash equilibrium (NE) in which both the user scheduling and power allocation strategy reach NE. Then, we design a distributed joint-strategy iterative algorithm to perform interference-aware resource allocation where only partial information exchange is involved. Simulation results demonstrate the effectiveness of the proposed algorithm.

Keywords Interference coordination · OFDMA networks · Uplink · Multi-cell · Joint game · Joint-strategy Nash equilibrium

1 Introduction

Inter-cell interference (ICI) is a major impairment that limits the system throughput in cellular OFDMA networks with aggressive frequency reuse [1]. Base station (BS) coopera-

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tion/coordination has emerged as a key technology to mitigate the inter-cell interference and improve the system throughput. In general, the coordination takes place at two different levels [2,3]. (i) The antennas across the multiple base stations (BSs) forms a large antenna array to jointly transmit and receive signals for multiple mobile users, which effectively enhances the received signal quality as well as decreases the received interference. However, in this fully coordinated network multiple-input multiple-output (MIMO) system, data streams of multiple users must be shared among the multiple BSs, which leads to high-capacity backhaul communication [2]; (ii) only resource allocation schemes and user transmission strategies, rather than data signals, are coordinated among the BSs. The level of coordination obviously requires much less message exchange, and thus is much easier for practical implementation [3].

This paper addresses the second level of BS coordination (a.k.a., the coordinated resource allocation) in cellular wireless networks. In the state of the art, both centralized and distributed procedures have been designed. Since most of the optimization problems in cellular networks can be proved to be NP-hard [1], standard optimization techniques do not apply directly and even centralized algorithms cannot guarantee that the globally optimal solution is found. In contrast, distributed algorithms (e.g., [1,4–6]) are more attractive as they do not require a central controller and may demand less information exchange and computational complexity. Moreover, distributed algorithms are often more adaptable to users joining and leaving the systems, and are more robust to network dynamics (e.g., channel fading in wireless networks) [7]. It is worth noting that “distributed” in this paper does not mean fully distributed algorithm without any information exchange [8,9], while it represents the distributed coordination with necessary message passing overheads [7,10].

In this paper, we make a distributed investigation on the joint user scheduling and power allocation problem in the uplink multi-cell OFDMA systems by resorting to game theory. It is noted that the existing works [1,4,6] mainly focus on downlink, while the uplink is much more complicated. Specifically, for downlink networks, the user scheduling when power allocation is fixed, is proved to be just a simple optimization problem for each cell without causing the variation of interference with other cells [4,6], which is a special property for cellular wireless networks. However, it is not the case for uplink where standard optimization techniques do not apply. The existing researches for uplink mainly focus on a single-cell OFDMA system where there is no co-channel interference [11,12]. In this deployment, the joint subchannel/subcarrier and power allocation problem can be proved to be a convex problem by continuously relaxing the subchannel allocation [13]. Then, standard convex optimization methods can be employed to achieve the optimal solution. However, the joint resource allocation in multi-cell network in the presence of the co-channel interference is a well-known combinatorial optimization problem, which is the focus of our work. Although [14] addresses the uplink multi-cell OFDMA network, the proposed subchannel assignment is centralized. In contrast, our work proposes a completely distributed scheme for both the power allocation and subchannel assignment.

It should be pointed out that game theoretic resource allocation schemes have been widely studied in the literature. In [8,9,15–17], game theoretic channel allocation algorithms are proposed for interference minimization. In [5,18], taking the inter-cell interference into account, the authors study the transmit power control in multi-cell OFDMA systems by using non-cooperative game. However, most of the existing game theoretic works consider a largely simplified system model and just concentrate on only one aspect (either power control or subchannel allocation). In [1], both subchannel assignment and power allocation are investigated by using game theory. However, the work is essentially decomposed into two subgames, in which the subchannel assignment and power control are performed separately and iteratively.

Since the subchannel assignment and power control are coupled with each other, it is intuitive to perform the two subproblems jointly in order to achieve a better solution. In this paper, we design a joint game simultaneously performing the two subproblems to further improve the performance. Specifically, each BS acts as a game player to automatically and independently update its user scheduling as well as power allocation strategy. By constructing a potential function, the formulated game is proved to have at least one joint-strategy NE, where no player (i.e., BS) will deviate from its joint strategy unilaterally.

The rest of this paper is organized as follows. In Sect. 2, we present our system model and problem formulation for inter-cell interference coordination. In Sect. 3, we formulate a joint game to address the user scheduling and power allocation simultaneously. In Sect. 4, we propose a distributed algorithm to compute the NE solution. In Sect. 5, we conduct numerical simulations to validate our analysis. Finally, this paper is concluded in Sect. 6.

2 System Model and Problem Formulation

2.1 System Model

We consider the uplink of an OFDMA multi-cell network with reuse factor one, which consists of a set of L BSs, denoted by $\mathcal{L} = \{1, 2, \dots, L\}$. We assume each of the cells is equipped with a BS and that BSs communicate with the users in a single-hop fashion. We also assume the BSs are time-synchronized. Base stations and users are equipped with one transmit and one receive antenna, respectively. $\mathcal{N} = \{1, 2, \dots, N\}$ is the user set. The set of users served by BS $l \in \mathcal{L}$ is denoted by \mathcal{N}_l , $\mathcal{N}_l \subseteq \mathcal{N}$, and $\bigcup_l \mathcal{N}_l = \mathcal{N}$. Each user is connected to only one BS that is selected based on long-term channel quality measurement. Thus, $\mathcal{N}_l \cap \mathcal{N}_{l'} = \emptyset$, for $l \neq l'$. The available spectrum is divided into K subchannels, and the index set of all subchannels is denoted by $\mathcal{K} = \{1, 2, \dots, K\}$. $N = |\mathcal{N}|$ and $K = |\mathcal{K}|$ is the cardinality of \mathcal{N} and \mathcal{K} , respectively.

Let $n(l, k) \in \mathcal{N}_l$ denote the user connected to base station l on subchannel k . When perfect synchronization is assumed, the discrete-time baseband signal received by user $n(l, k)$ on subchannel k is given by

$$r_{n(l,k)} = \underbrace{H_{n(l,k),l}x_{n(l,k)}}_{\text{useful data}} + \underbrace{\sum_{i=1, i \neq l}^L H_{n(i,k),l}x_{n(i,k)}}_{\text{intercell interference}} + \underbrace{Z_{n(l,k)}}_{\text{noise}}, \tag{1}$$

where $x_{n(l,k)}$ and $H_{n(l,k),l}$ denote the transmitted complex symbol and the channel response from the user $n(l, k)$ to the BS l , respectively. In addition, $Z_{n(l,k)}$ is the additional noise, which is modeled as a white Gaussian variable with power $\mathbb{E} |Z_{n(l,k)}|^2 = \sigma^2$.

2.2 Problem Formulation

We now turn to the core problem of resource allocation. Similar to [19], the resource allocation problem considered here consists of user scheduling and power allocation subproblems. Importantly we concentrate on rate maximizing resource allocation schemes, rather than fairness-oriented ones. In this setting, the optimization of resources in various spectral resource slots (i.e., frequency bands, or subchannels) decouples, and we may consider the user scheduling and power allocation which maximize the capacity in a particular slot, inde-

pendent of others [19]. On any given spectral resource slot shared by all cells, we denote the user scheduled in cell l by $n_l \in \mathcal{N}_l$.

Definition 1 A *scheduling vector* contains the set of users simultaneously scheduled across all cells in the same subchannel: $\mathbf{S} = [n_1 n_2 \dots n_l \dots n_L]$, where $[\mathbf{S}]_l = n_l$. Noting that $n_l \in \mathcal{N}_l$, the constraint set of scheduling vectors (i.e., the scheduling strategy space) is given by $\mathbb{S} = \{\mathbf{S} | n_l \in \mathcal{N}_l, \forall l = 1, \dots, L\}$.

Definition 2 A *transmit power vector* contains the transmit power values used by each scheduled user to communicate with its respective BS: $\mathbf{P} = [P_{n_1} P_{n_2} \dots P_{n_l} \dots P_{n_L}]$, where $[\mathbf{P}]_l = P_{n_l}$. Due to the peak power constraint $0 \leq P_{n_l} \leq P_{n_l}^{\max}$, the constraint set of transmit power vectors is given by $\mathbb{P} = \{\mathbf{P} | 0 \leq P_{n_l} \leq P_{n_l}^{\max}, \forall l = 1, \dots, L\}$. Although the above bound reveals to be not tight owing to the decoupling of the subchannels, it does not impact the following theoretical analysis and the strict power constraint of each user will be considered in designing of the algorithm in Sect. 4.

The signal-to-interference-plus-noise ratio (SINR) experienced by the user n_l in cell l is given by

$$\gamma_l(\mathbf{S}, \mathbf{P}) = \frac{P_{n_l} G_{n_l, l}}{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}, \tag{2}$$

where $G_{n_i, l} = |H_{n_i, l}|^2$ is the channel power gain from user n_i to the base station l . The corresponding achievable information rate (in bits per channel use) is given by the following Shannon’s formula:

$$R_l(\mathbf{S}, \mathbf{P}) = \log_2 \left(1 + \frac{\gamma_l(\mathbf{S}, \mathbf{P})}{\Gamma} \right), \tag{3}$$

where $\Gamma = -\ln(5\text{BER})/1.5$ is the bit error rate (BER) gap.

From the system optimization point of view, the sum-rate optimal resource allocation problem can now be formalized as

$$(\mathbf{S}^{opt}, \mathbf{P}^{opt}) = \arg \max_{\mathbf{S} \in \mathbb{S}, \mathbf{P} \in \mathbb{P}} \sum_{l=1}^L R_l(\mathbf{S}, \mathbf{P}), \tag{4}$$

3 Joint Game for Interference Coordination

In this section, we study the distributed solution of the above problem (4). The ability to model individual, independent decision makers, whose strategies are interactional, makes game theory particularly attractive to analyze the performance of decentralized network/framework.

3.1 Game Model

Formally, the game is denoted by $G = [\mathcal{L}, \{\mathcal{A}_l\}_{l \in \mathcal{L}}, \{u_l\}_{l \in \mathcal{L}}]$, where $\mathcal{L} = \{1, 2, \dots, L\}$ is the set of players (i.e., BSs), \mathcal{A}_l is the set of available actions for player l , and u_l is the utility function of player l , which is defined as

$$u_l(A_l, A_{-l}) = -\frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{P_{n_l} G_{n_l, l}} - \sum_{i=1, i \neq l}^L \frac{P_{n_l} G_{n_l, i}}{P_{n_i} G_{n_i, i}}, \tag{5}$$

where $A_l \in \mathcal{A}_l$ is the joint strategy of player l , $A_l = S_l \times P_{n_l}$, and $A_{-l} \in \mathcal{A}_1 \times \dots \times \mathcal{A}_{l-1} \times \mathcal{A}_{l+1} \times \dots \times \mathcal{A}_L$ represents a strategy profile of all the players excluding l , where \times denotes the Cartesian product. In addition, λ_l is the cost factor.

Definition 3 (*Nash equilibrium*) A resource allocation profile $A^* = (A_1^*, \dots, A_L^*)$ is a pure strategy NE point of G if and only if no player can improve its utility by deviating unilaterally, i.e.,

$$u_l(A_l^*, A_{-l}^*) \geq u_l(A'_l, A_{-l}^*), \forall l \in \mathcal{L}, \quad \forall A'_l \in \mathcal{A}_l \setminus \{A_l^*\}. \tag{6}$$

3.2 Analysis of NE

Theorem 1 G is an exact potential game.

Proof We Following the similar lines of proof in [8,21], we define a network potential function for the joint strategy game G as $F(A_l, A_{-l}) = -\sum_{l=1}^L \frac{1}{\gamma_l}$. According to (2), we can get

$$\begin{aligned} F(A_l, A_{-l}) &= -\sum_{l=1}^L \frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{P_{n_l} G_{n_l, l}} \\ &= -\frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{P_{n_l} G_{n_l, l}} - \sum_{j=1, j \neq l}^L \frac{\sum_{i=1, i \neq j}^L P_{n_i} G_{n_i, j} + \sigma^2}{P_{n_j} G_{n_j, j}} \\ &= -\frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{P_{n_l} G_{n_l, l}} - \sum_{j=1, j \neq l}^L \frac{P_{n_l} G_{n_l, j}}{P_{n_j} G_{n_j, j}} - \sum_{j=1, j \neq l}^L \frac{\sum_{i=1, i \neq j, i \neq l}^L P_{n_i} G_{n_i, j} + \sigma^2}{P_{n_j} G_{n_j, j}} \\ &= u_l(A_l, A_{-l}) - v(A_{-l}) \end{aligned} \tag{7}$$

where $v(A_{-l}) = \sum_{j=1, j \neq l}^L \frac{\sum_{i=1, i \neq j, i \neq l}^L P_{n_i} G_{n_i, j} + \sigma^2}{P_{n_j} G_{n_j, j}}$ is independent of A_l . Thus, if an arbitrary player, e.g., player l , unilaterally changes its strategy from A_l to A'_l , then we have

$$F(A'_l, A_{-l}) = u_l(A'_l, A_{-l}) - v(A_{-l}). \tag{8}$$

Then, according to (7) and (8), we can get

$$F(A'_l, A_{-l}) - F(A_l, A_{-l}) = u_l(A'_l, A_{-l}) - u_l(A_l, A_{-l}). \tag{9}$$

It can be seen from (9) that the change in individual utility function caused by any player’s unilateral deviation is equal to the change in the potential function. Therefore, according to the definition given in [20], G is an exact potential game with potential function F . This completes the proof. \square

Remark 1 Exact potential game belongs to potential games, which have been broadly applied to wireless communication systems [8,9,16,21,22]. It exhibits several nice properties and the most important two are:

- Potential games have at least one pure NE point.
- All Nash equilibria are the maximizers of the potential function F , either locally or globally.

Table 1 Joint-strategy iteration algorithm

Initialization

$t = 1$, assign a random channel allocation profile and each user allocates its power uniformly in each subchannel.

Iteration Process:

Repeat

$t = t + 1$;

for subchannel $k = 1 : K$

Fix the power at the value updated in the last iteration, each player (BS) sequentially chooses a best response according to

$$S_l^t = \arg \max_{S_l \in \mathbb{S}_l, \mathbf{P} = \mathbf{P}^{t-1}} u_l(S_l, S_{-l}^{t-1}),$$

and then updates its power strategy based on the user scheduling profile according to

$$P_{n_l, k}^* = \arg \max_{P_{n_l, k} \in \mathbb{P}_{n_l}, \mathbf{S} = \mathbf{S}^t} u_l(P_{n_l, k}, P_{-n_l, k}^{t-1}),$$

$$P_{n_l, k}^t \leftarrow P_{n_l, k}^{t-1} + \delta \cdot \left(\min \left(P_{n_l, k}^*, P_{n_l, k}^t \right) - P_{n_l, k}^{t-1} \right)$$

where $P_{n_l, k}^t = P_{n_l}^{\max} - \sum_{k' \in \Omega_{n_l}, k' \neq k} P_{n_l, k'}^t$ is for the maximal

power constraint of each user, and Ω_{n_l} is the subchannel set of user n_l , $\delta > 0$ is a fixed step size.

end for

Until $(A^t = A^{t-1})$

4 Implementation of Joint Game

In this section, we propose a distributed algorithm to compute the equilibrium solutions to problem formulated in (4). The procedure is run before the start of each scheduling interval, in which the user scheduling and transmit power of each BS are updated through distributed iteration.

4.1 Algorithm Description

Although we have verified the existence of the joint strategy NE in Sect. 3, still, it is very difficult to implement the joint game in practical scenarios. Because the strategy set of user scheduling is discrete while the strategy set of power allocation is continuous, efficient selection of a better/best 2-dimensional joint strategy is not an easy work in each iteration. Therefore, we design a decomposed iteration process illustrated in Table 1¹ which could be implemented easily and can also guarantee the convergence to the joint-strategy NE point, which will be proved in Sect. 4.2. In each iteration, since the size of the strategy set is just the number of scheduled users, the selection of a best user scheduling strategy is easy. In contrast, to find the optimal power from the continuous power strategy set, we should take the derivative of the utility function with respect to the transmit power P_{n_l} , then equalize it to zero, that is,

¹ In the algorithm, subscript k is added to distinguish different subchannels.

$$\frac{\partial u_l}{\partial P_{n_l}} = \frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{P_{n_l}^2 G_{n_l, l}} - \sum_{i=1, i \neq l}^L \frac{G_{n_l, i}}{P_{n_i} G_{n_i, i}} = 0. \tag{10}$$

Then, we can get the optimal power strategy

$$P_{n_l}^* = \sqrt{\frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{G_{n_l, l} \sum_{i=1, i \neq l}^L \frac{G_{n_l, i}}{P_{n_i} G_{n_i, i}}}}. \tag{11}$$

In consideration of fairness in terms of the power allocated in each subchannel, the power allocation strategy in the algorithm is updated by a step size (i.e., the gradient-play dynamic). Moreover, it is easier to find the globally optimal point.

Remark 2 In the proposed algorithm shown in Table 1, each BS independently and automatically makes decisions about its user scheduling and power allocation strategy. Thus, the proposed algorithm is distributed, since distributed algorithms are characterized by parallel processing by different network elements in the network. In addition, necessary information (e.g., channel state information, user transmission strategies) needs to be exchanged among BSs, which is a reflection of the BS cooperation. Since data signals do not need to be coordinated among the BSs, this level of coordination obviously requires much less message exchange [2,3], and thus is much easier for practical implementation.

Remark 3 Due to the spectral diversity, the optimal user scheduling and power allocation schemes in different subchannels are usually different. Therefore, we should use a repetitive operation to recompute the user scheduling S_l as well as power allocation in different subchannels, as shown in the proposed algorithm.

With the presence of path loss, it is likely that most of the subchannels will be allocated to users who are closer to the BS. However, we can achieve fairness among users by adding a weight factor to this utility function as

$$u_l = -\omega_{n_l} \left(\frac{\sum_{i=1, i \neq l}^L P_{n_i} G_{n_i, l} + \sigma^2}{P_{n_l} G_{n_l, l}} \right) - \sum_{i=1, i \neq l}^L \omega_{n_i} \frac{P_{n_l} G_{n_l, i}}{P_{n_i} G_{n_i, i}}, \tag{12}$$

where ω_{n_l} is the weight of the scheduled user in the l th cell. Following the similar lines of proof in Theorem 1, we can prove that the corresponding potential function is $F = -\sum_{l=1}^L \omega_{n_l} \cdot \frac{1}{\gamma_l}$. Note that there is a tradeoff between fairness and optimality. The best policy of selecting the user weights is outside the scope of this paper. For simplicity, ω_{n_l} is set to be $\omega_{n_l} = \frac{G_{n_l, l}}{\sum_{n_i \in \mathcal{N}_l} G_{n_i, l}}$ in this paper. When user n_l possesses a better channel gain $G_{n_l, l}$ (usually for users closer to BS), its assigned weight factor ω_{n_l} will be larger, and thus it will be less likely to be scheduled since the utility function is negative. In this way, fairness among users can be improved.

4.2 Convergence Analysis and Practical Implementation

It is obvious that for exact potential games with the finite improvement property, the myopic learning process based on the one-sided better/best reply dynamic converges to the equilibrium set [20]. The improvement in individual’s utility leads to the improvement of network performance until stability (i.e., NE) is reached. In our algorithm, although the user scheduling and power allocation strategy updating is decomposed into two steps, no decrease of system utility in each step is guaranteed. Therefore, it must converge to the NE point.

The implementation of the power allocation can be shifted from the base station to each user and the convergence to NE can be still guaranteed. Thus, the control signal exchange between BSs and users can be largely reduced. Users can adjust their transmit power by themselves. In addition, also because the joint game is a exact potential game, the user scheduling and the transmit power allocation can be updated asynchronously, and the convergence can also be fulfilled.

5 Simulation Results

In this section, we conduct simulations to study the performance of the proposed algorithm. We consider a 3-cell OFDMA system, where each hexagonal cell has a radius of 100 m similar to the case in [5] and the users are generated as a uniform distribution within the corresponding cell. The base stations are located at the center of each cell and are separated by $100\sqrt{3}$ m from each other. The number of users in each cell is 4. The path loss between user $n(i, k)$ and BS l is expressed as $h_{n(i,k),l} = 1/d_{n(i,k),l}^\nu$, where $\nu = 4$, and $d_{n(i,k),l}$ is the distance between user $n(i, k)$ and BS l . Then the channel gain is $G_{n(i,k),l} = h_{n(i,k),l} |\beta_k|^2$, where $\beta_k \sim \mathcal{CN}(0, 1)$ is a unitary power, Rayleigh fading coefficient [19]. The total bandwidth B is divided into $M = 64$ subchannels. For simplicity, we set $\Gamma = 1$. The Gaussian noise variance σ^2 is 10^{-10} W. The step size δ is set to be 0.01.

Figure 1 plots the system sum-rate improvement versus the number of iterations when the maximal power constraint of each user is set to be $P_{\max} = 20$ mW. The proposed joint game approach and the two-stage game approach [1] are compared. As it can be clearly seen from the figure, the sum-rate value is updated at each iteration and greatly improved at the convergence time. Moreover, the performance of the joint game outweighs that of the two-stage game. In terms of computation complexity, both are on the scale of $O(N)$. The number of iterations needed for convergence of the two-stage game is almost the double of that of joint game, while joint game algorithm performs two operations in one iteration quickly.

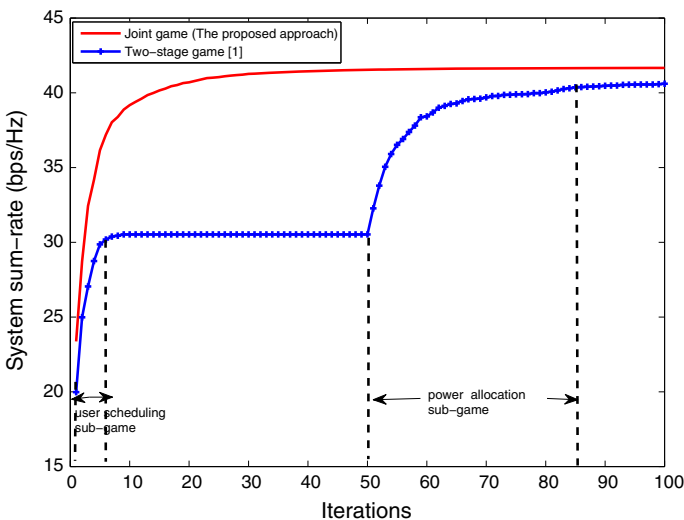


Fig. 1 System sum-rate improvement versus the number of iterations

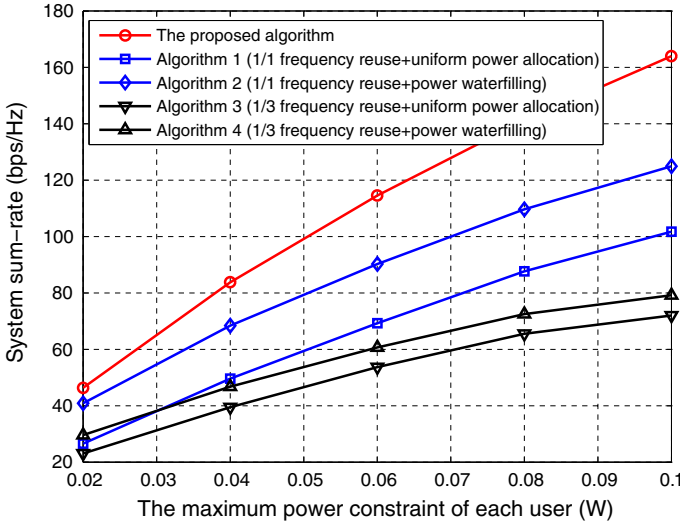


Fig. 2 System sum-rate comparison when the user’s maximum power constraint P_{max} varies

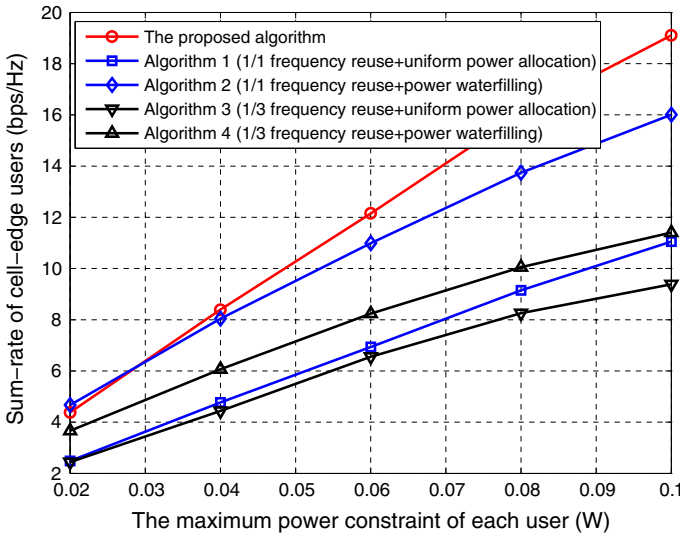


Fig. 3 Sum-rate comparison of cell-edge users when the user’s maximum power constraint P_{max} varies

Figures 2, 3 and 4 present algorithm comparison in terms of system sum-rate, sum-rate of cell-edge users and fairness among users, respectively. For comparison, the following algorithms are considered: (i) Algorithms 1 and 3: each user is assigned the same number of subchannels and then the power is uniformly allocated, (ii) Algorithms 2 and 4: each user is assigned the same number of subchannels, but the power allocation is through iterative water-filling algorithm [23]. Moreover, Algorithms 1 and 2 adopt the 1/1 frequency reuse scheme [24], while Algorithms 3 and 4 consider the traditional 1/3 frequency reuse scheme [24].

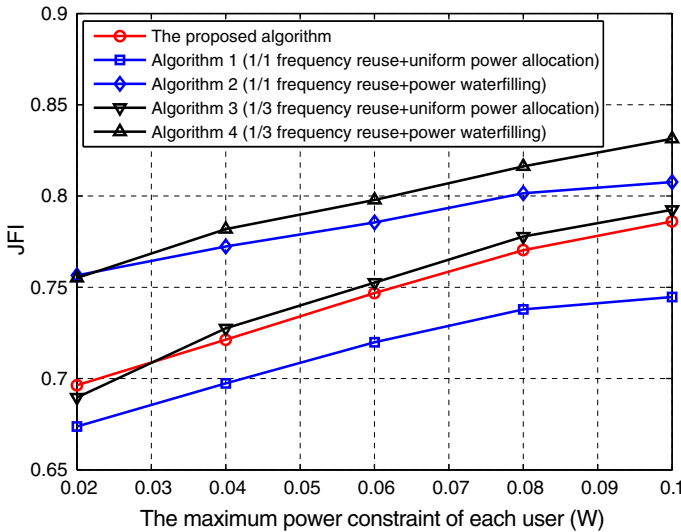


Fig. 4 Fairness comparison when the user’s maximum power constraint P_{max} varies

In Fig. 2, we presents system sum-rate comparison when the user’s maximum power constraint P_{max} varies from 10 to 100mW. As shown in the figure, Algorithms 1 and 2 are both better than Algorithms 3 and 4, which indicates that 1/1 frequency reuse scheme achieves a higher system capacity than 1/3 frequency reuse scheme. Moreover, the network water-filling algorithm is better than the uniform power allocation scheme. Besides, our proposed algorithm can achieve the largest system capacity, and the performance gap with other algorithms becomes larger when the transmit power of users increases.

Figure 3 presents the sum-rate of cell-edge users obtained by different algorithms. The overall characteristics of the curves are similar to that in Fig. 2, except for two special results: (i) Algorithm 4 is better than Algorithm 1, and (ii) Algorithm 2 achieves larger cell-edge sum-rate than our proposed algorithm when the transmit power of users is low. In addition, Fig. 4 evaluate the fairness among users by different algorithms. Here we analyze the fairness by

using Jain’s fairness index (JFI) [25], which is defined by $J = \frac{(\sum_{i=1}^N R_i)^2}{N \sum_{i=1}^N (R_i)^2}$, where R_i denotes the rate of user i . It is noted that JFI translates a resource allocation vector $\{R_1, R_2, \dots, R_N\}$ into a score in the interval of $[1/N, 1]$ and a higher JFI indicates a fairer resource allocation scheme. We can see from Fig. 4 that the 1/3 frequency reuse scheme achieves higher JFI than 1/1 frequency reuse scheme. Besides, the proposed algorithm does not show very fair resource allocation, which is only better than Algorithm 1. However, it is worth noting that the proposed algorithm achieves larger system capacity, as shown in Fig. 2. Therefore, there is a tradeoff between fairness and the system capacity. How to balance the two metrics is an interesting research topic, which is outside the scope of this paper.

6 Conclusion

In this paper, we investigated the distributed solution of the coordinated resource allocation with interference awareness in uplink multi-cell OFDMA networks. The problem was modeled as an exact potential game and the existence of NE was proved. Then we proposed

a joint-strategy iterative algorithm to perform user scheduling and power allocation simultaneously, which was proved to converge to the joint-strategy NE. The simulation results demonstrated its good convergence and significant throughput gain over uncoordinated allocation schemes as well as two-stage game approach.

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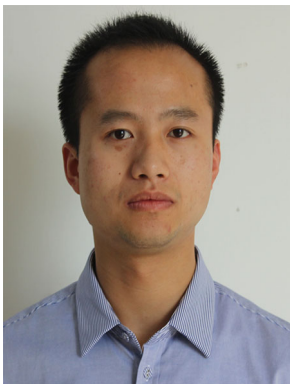
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